

A Network Tour of Data Science (NTDS)

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DEEP LEARNING ON GRAPHS

LEARNING BEYOND EUCLIDEAN DATA

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Structured data

Majority of data is naturally unstructured, but can be structured.

Why structure data ?

- ▶ To incorporate additional information.
- ▶ To regularize the learning process.
- ▶ To decrease learning complexity by making geometric assumptions.

Data structured by Euclidean grids.

- ▶ 1D: sound, time-series.
- ▶ 2D: images.
- ▶ 3D: video, hyper-spectral images.

Non-Euclidean data: natural graphs

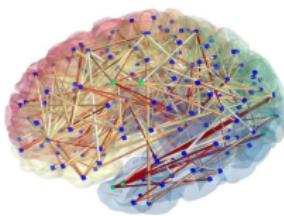
Modeling versatility: graphs model heterogeneous pairwise relationships

Examples of irregular / graph-structured data:

- ▶ Social networks: Facebook, Twitter.
- ▶ Biological networks: genes, molecules, brain connectivity.
- ▶ Infrastructure networks: energy, transportation, Internet, telephony.



Social network



Brain structure



Telecommunication

Non-Euclidean data: constructed graphs

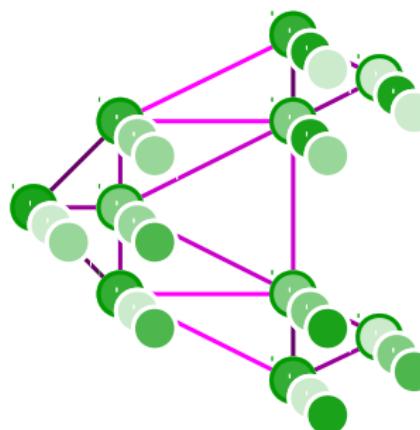
Sample graph

- ▶ Semi-supervised learning.
- ▶ Incorporate external information.

Feature graph

- ▶ Reduce computations.
- ▶ Incorporate external information.

○ document
— citation
— hyper-link
○ words



○ word
— similarity
○ documents

Using the structure: bridging graphs & neural networks

Extrinsic: embed the graph in an Euclidean space.

- ▶ Each node is represented by a vector.
- ▶ Use that embedding as additional features for a fully connected NN.
- ▶ Use a convolutional NN in the embedding space.
Possibly very high-dimensional!

Intrinsic: a Neural Net working on graph-structured data.

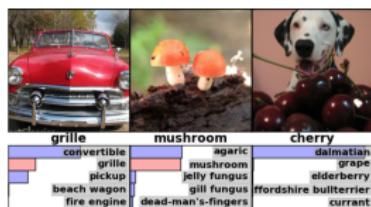
- ▶ Exploit geometric structure for computational efficiency.
- ▶ Starting point: ConvNets, an intrinsic formulation for Euclidean grids.

ConvNets are ubiquitous

LeCun, Bengio, and Hinton 2015

First developed for Computer Vision

- ▶ Object recognition
- ▶ Image captioning
- ▶ Image inpainting



Spreading outside CV

- ▶ Natural language processing
- ▶ Audio: sound & voice
- ▶ Autonomous agents (playing Atari or Go)

Why are ConvNets good ?

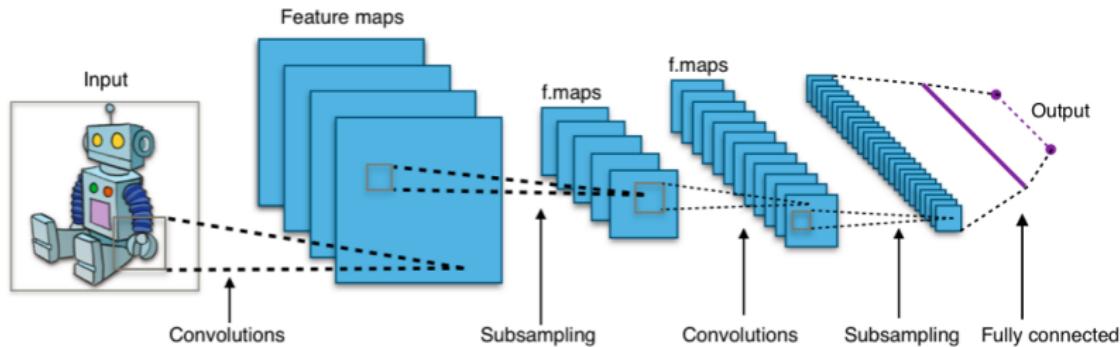
ConvNets are extremely efficient at extracting meaningful statistical patterns in large-scale and high-dimensional datasets.

Because they make use of the underlying structure in the data.

Statistical assumptions

- ▶ **Localization**: compact filters for low complexity
- ▶ **Stationarity**: translation invariance
- ▶ **Compositionality**: analysis with a filterbank

ConvNets: architecture



Ingredients

1. Convolution
2. Non-linearity (ReLU)
3. Down-sampling
4. Pooling

ConvNets: feature extraction

Zeiler and Fergus 2014

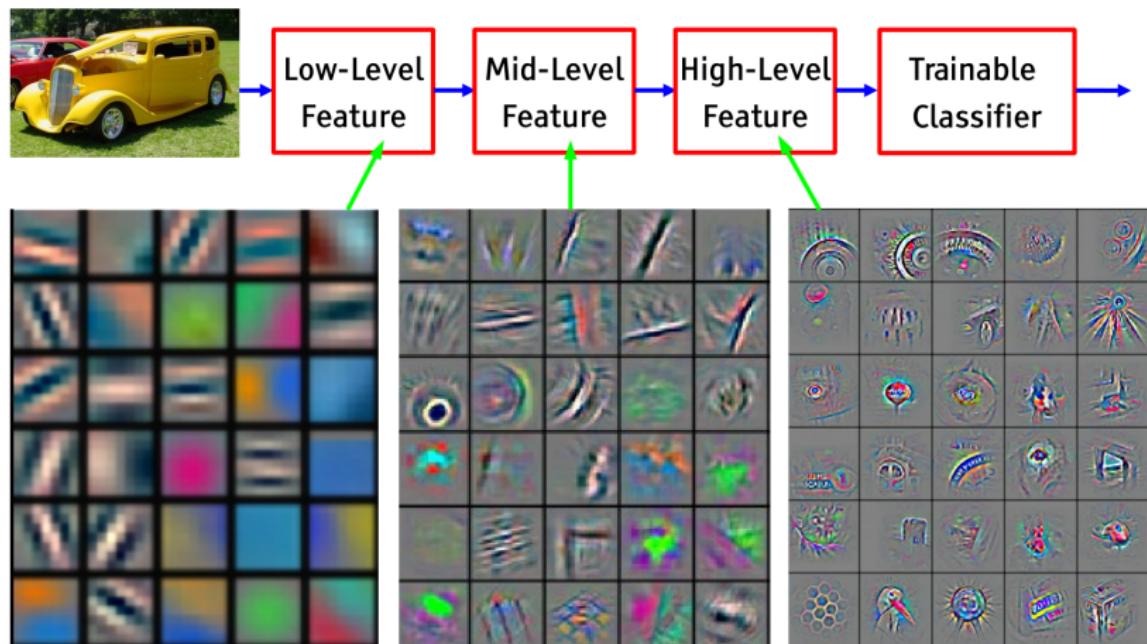


Figure: Features extracted from ImageNet

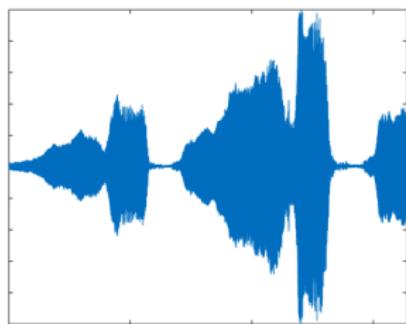
Developed for data lying on Euclidean grids

All operations are well defined and computationally efficient:

1. Convolution → filter translation or fast Fourier transform (FFT).
2. Down-sampling → pick one pixel out of n .



Image (2D) Video (3D)

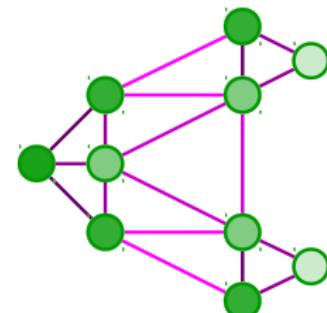
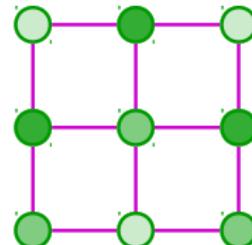


Sound (1D)

ConvNets on graphs

Graphs vs Euclidean grids

- ▶ Irregular sampling.
- ▶ Weighted edges.
- ▶ No orientation (in general).



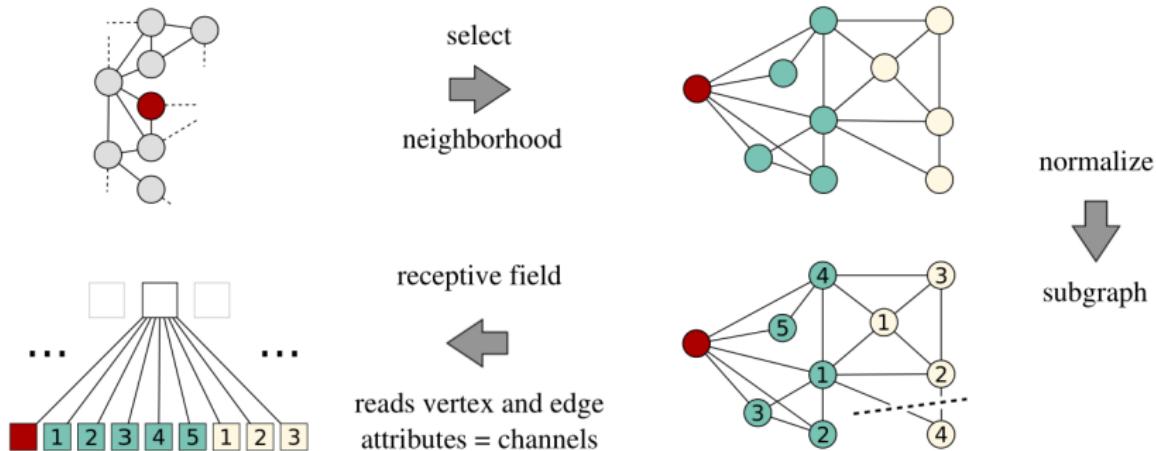
Challenges

1. Formulate convolution and down-sampling on graphs.
2. Make them efficient!

ConvNets on graphs: spatial approach

Niepert, Ahmed, and Kutzkov 2016

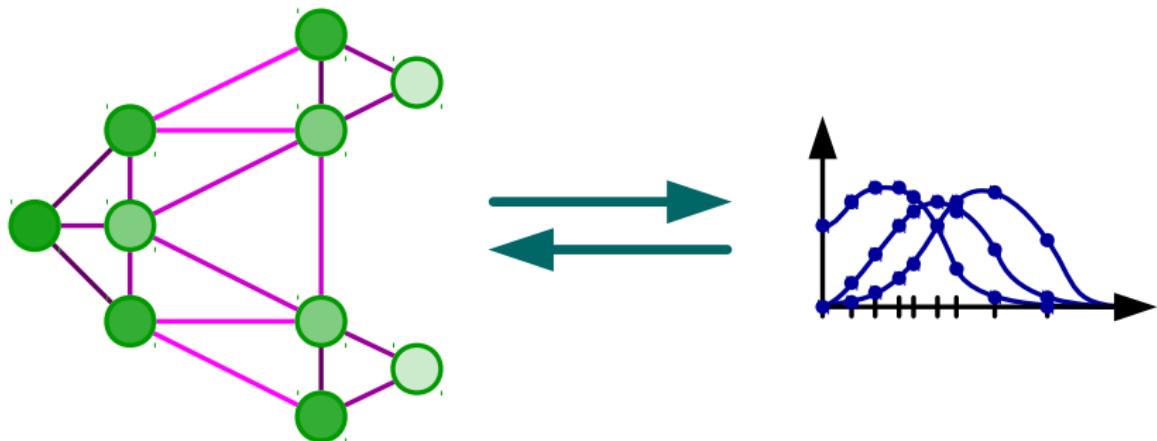
1. Define receptive field / neighborhood.
2. Order nodes.



ConvNets on graphs: spectral approach

Bruna, Zaremba, Szlam, and LeCun 2014; Henaff, Bruna, and LeCun 2015

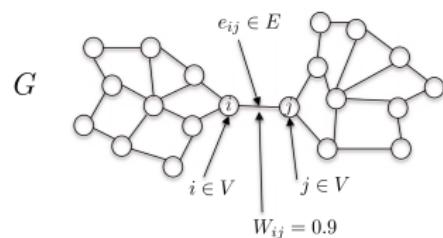
- ▶ Spectral graph theory for convolution on graphs.
- ▶ Balanced cut model for graph coarsening (sub-sampling).



Definitions: graph

Chung 1997

$\mathcal{G} = (\mathcal{V}, \mathcal{E}, W)$: undirected and connected graph



- ▶ \mathcal{V} : set of $|\mathcal{V}| = n$ vertices
- ▶ \mathcal{E} : set of edges
- ▶ $W \in \mathbb{R}^{n \times n}$: weighted adjacency matrix
- ▶ $D_{ii} = \sum_j W_{ij}$: diagonal degree matrix

Graph Laplacians (core operator to spectral graph theory):

- ▶ $L = D - W \in \mathbb{R}^{n \times n}$: combinatorial
- ▶ $L = I_n - D^{-1/2} W D^{-1/2}$: normalized

Definitions: graph Fourier transform

Shuman, Narang, Frossard, Ortega, and Vandergheynst 2013

L is symmetric and positive semidefinite $\rightarrow L = U \Lambda U^T$ (EVD)

► Graph Fourier basis $U = [u_0, \dots, u_{n-1}] \in \mathbb{R}^{n \times n}$

► Graph “frequencies” $\Lambda = \begin{bmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_n \end{bmatrix} \in \mathbb{R}^{n \times n}$

Graph Fourier Transform

1. Graph signal $x : \mathcal{V} \rightarrow \mathbb{R}$ seen as $x \in \mathbb{R}^n$
2. Transform: $\hat{x} = \mathcal{F}_{\mathcal{G}}\{x\} = U^T x \in \mathbb{R}^n$
3. Inverse: $x = U\hat{x} = UU^T x = x$

Definitions: convolution on graphs

Shuman, Narang, Frossard, Ortega, and Vandergheynst 2013

Convolution theorem:

$$\begin{aligned} x *_{\mathcal{G}} g &= U (U^T g \odot U^T x) \\ &= U (\hat{g} \odot U^T x) \end{aligned}$$

Conveniently written as:

$$\begin{aligned} x *_{\mathcal{G}} g &= U \begin{bmatrix} \hat{g}(\lambda_1) & & 0 \\ & \ddots & \\ 0 & & \hat{g}(\lambda_n) \end{bmatrix} U^T x \\ &= U \hat{g}(\Lambda) U^T x \\ &= \hat{g}(L) x \end{aligned}$$

Spectral filtering of graph signals

$$y = \hat{g}_\theta(L)x = U\hat{g}_\theta(\Lambda)U^T x$$

Non-parametric filter:

$$\hat{g}_\theta(\Lambda) = \text{diag}(\theta), \theta \in \mathbb{R}^n$$

- ▶ Non-localized in vertex domain
- ▶ Learning complexity in $\mathcal{O}(n)$
- ▶ Computational complexity in $\mathcal{O}(n^2)$ (& memory)

Polynomial parametrization for localized filters

Shuman, Ricaud, and Vandergheynst 2016

$$\hat{g}_\theta(\Lambda) = \sum_{k=0}^{K-1} \theta_k \Lambda^k, \quad \theta \in \mathbb{R}^K$$

- ▶ Value at j of g_θ centered at i : $(\hat{g}_\theta(L)\delta_i)_j = (\hat{g}_\theta(L))_{i,j} = \sum_k \theta_k (L^k)_{i,j}$
- ▶ $d_{\mathcal{G}}(i,j) > K$ implies $(L^K)_{i,j} = 0$
(Hammond, Vandergheynst, and Gribonval 2011, Lemma 5.2)
- ▶ K -localized
- ▶ Learning complexity in $\mathcal{O}(K)$
- ▶ Computational complexity in $\mathcal{O}(n^2)$

Filter localization

Shuman, Ricaud, and Vandergheynst 2016

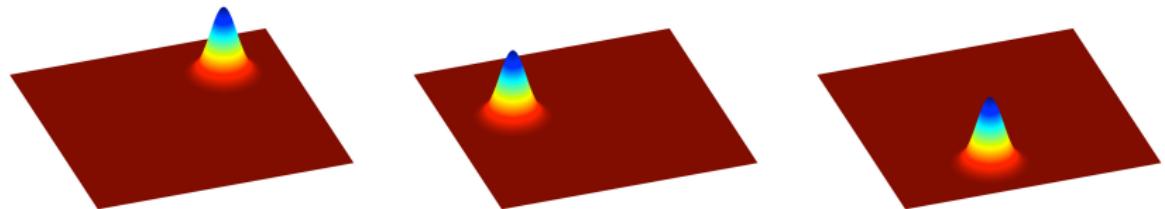


Figure: Localization on regular Euclidean grid.

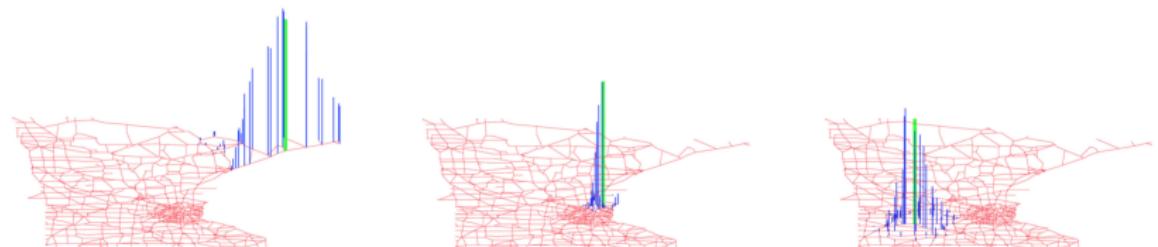


Figure: Localization on graph with $(\hat{g}_\theta(L)\delta_i)_j = (\hat{g}_\theta(L))_{i,j}$.

Recursive formulation for fast filtering

Hammond, Vandergheynst, and Gribonval 2011

$$\hat{g}_\theta(\Lambda) = \sum_{k=0}^{K-1} \theta_k T_k(\tilde{\Lambda}), \quad \tilde{\Lambda} = 2\Lambda/\lambda_{max} - I_n$$

- ▶ Chebyshev polynomials: $T_k(x) = 2xT_{k-1}(x) - T_{k-2}(x)$ with $T_0 = 1$ and $T_1 = x$
- ▶ Filtering: $y = \hat{g}_\theta(L)x = \sum_{k=0}^{K-1} \theta_k T_k(\tilde{L})x$
- ▶ Recurrence: $y = \hat{g}_\theta(L)x = [\bar{x}_0, \dots, \bar{x}_{K-1}]\theta$,
 $\bar{x}_k = T_k(\tilde{L})x = 2\tilde{L}\bar{x}_{k-1} - \bar{x}_{k-2}$ with $\bar{x}_0 = x$ and $\bar{x}_1 = \tilde{L}x$
- ▶ K -localized
- ▶ Learning complexity in $\mathcal{O}(K)$
- ▶ Computational complexity in $\mathcal{O}(K|\mathcal{E}|)$ (same as classical ConvNets!)

Learning filters

Defferrard, Bresson, and Vandergheynst 2016

$$y_{s,j} = \sum_{i=1}^{F_{in}} \hat{g}_{\theta_{i,j}}(L) x_{s,i} \in \mathbb{R}^n$$

- ▶ $x_{s,i}$: feature map i of sample s
- ▶ $\theta_{i,j}$: trainable parameters
($F_{in} \times F_{out}$ vectors of Chebyshev coefficients)

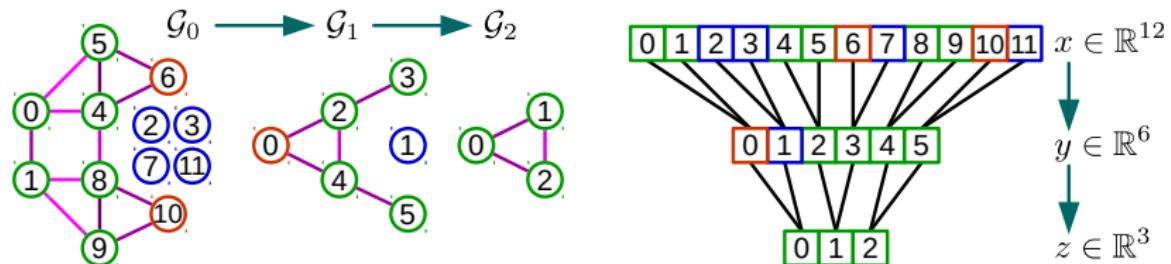
Gradients for backpropagation:

- ▶ $\frac{\partial E}{\partial \theta_{i,j}} = \sum_{s=1}^S [\bar{x}_{s,i,0}, \dots, \bar{x}_{s,i,K-1}]^T \frac{\partial E}{\partial y_{s,j}}$
- ▶ $\frac{\partial E}{\partial x_{s,i}} = \sum_{j=1}^{F_{out}} g_{\theta_{i,j}}(L) \frac{\partial E}{\partial y_{s,j}}$

Overall cost of $\mathcal{O}(K|\mathcal{E}|F_{in}F_{out}S)$ operations

Coarsening & Pooling

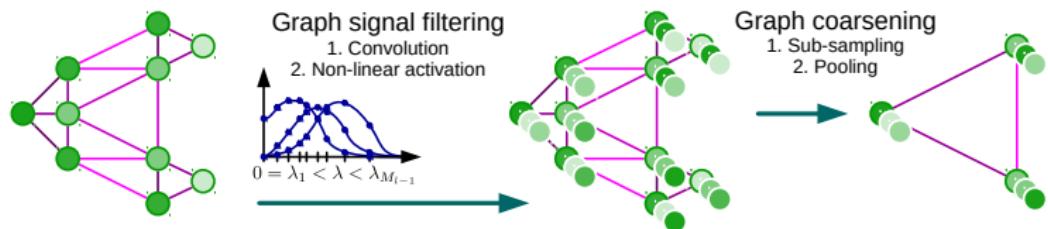
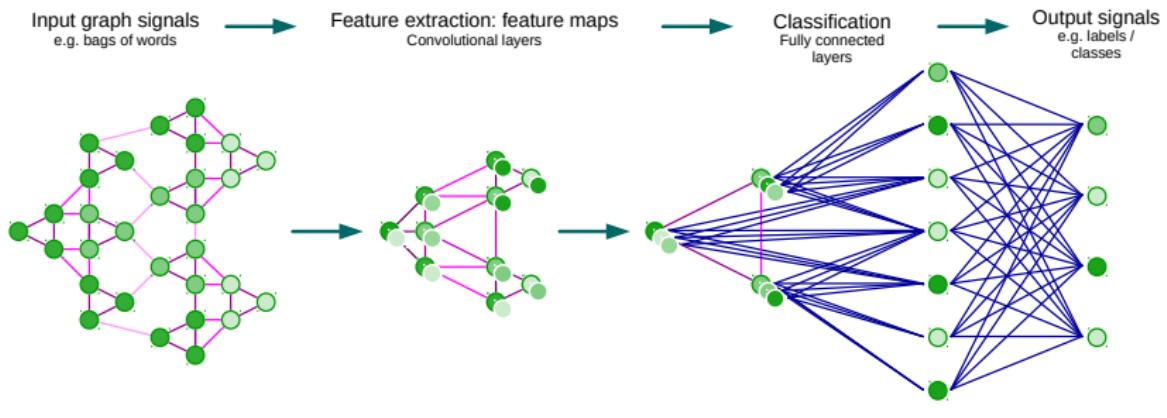
Defferrard, Bresson, and Vandergheynst 2016



- ▶ **Coarsening:** Graclus / Metis
 - ▶ Approximate normalized cut minimization.
- ▶ **Pooling:** as regular 1D signals
 - ▶ Binary tree structured coarsened graphs.
 - ▶ Satisfies parallel architectures like GPUs.
- ▶ **Activation:** ReLU, LeakyReLU, maxout, tanh, sigmoid.

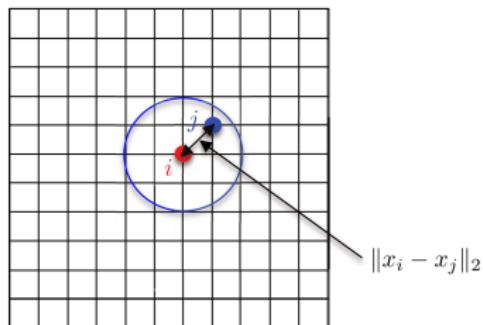
Graph ConvNet architecture

Defferrard, Bresson, and Vandergheynst 2016



MNIST: revisiting Euclidean ConvNets

5	3	7	3	1	9	0	5	4	5
0	8	2	3	2	0	6	7	8	1
3	1	7	3	4	5	6	2	4	9
0	4	2	1	8	9	6	7	3	5
6	1	9	3	4	5	4	9	2	9
0	7	2	3	6	5	6	7	8	8



$$W_{ij} = e^{-\|x_i - x_j\|_2^2 / \sigma}$$

MNIST: classification accuracy

Model	Architecture	Accuracy
Classical CNN	C32-P4-C64-P4-FC512	99.33
Proposed graph CNN	GC32-P4-GC64-P4-FC512	99.14

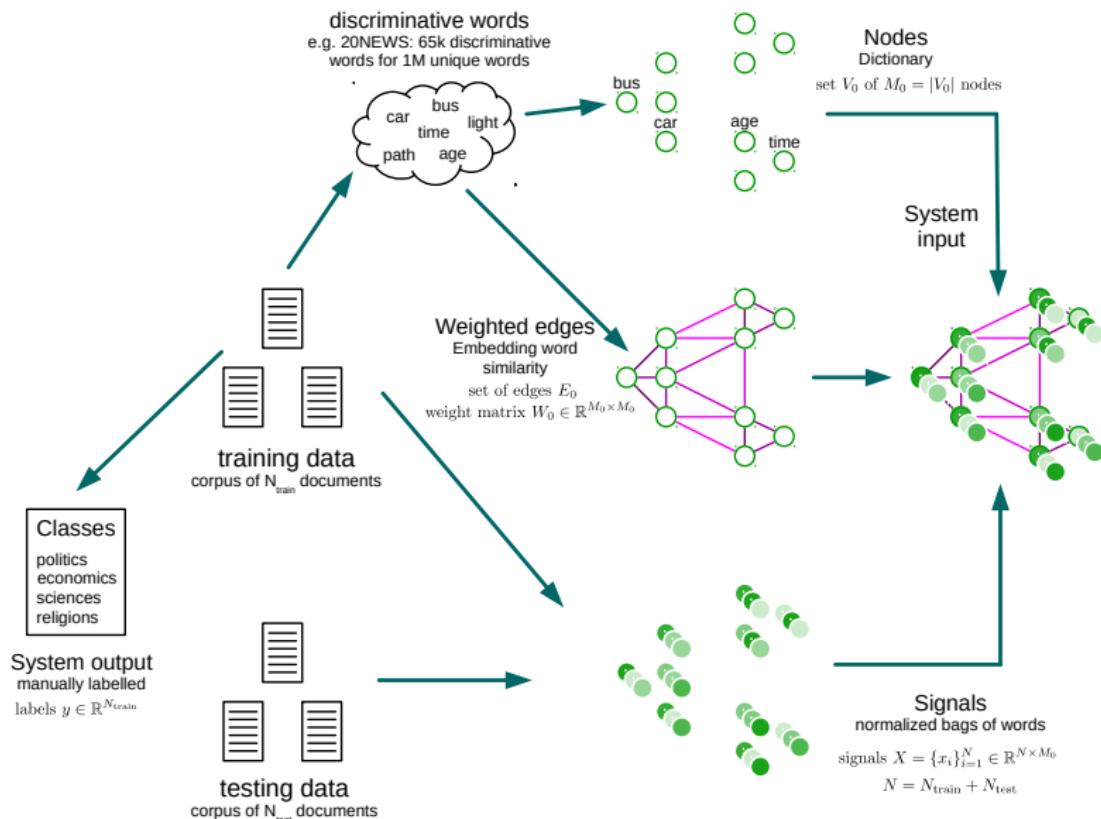
Comparison to classical CNNs.

Comparable to classical ConvNets!

Isotropic filters → rotation invariance

20NEWS: structuring documents with a feature graph

Defferrard, Bresson, and Vandergheynst 2016



20NEWS: graph quality

	word2vec			
bag-of-words	pre-learned	learned	approximate	random
67.50	66.98	68.26	67.86	67.75

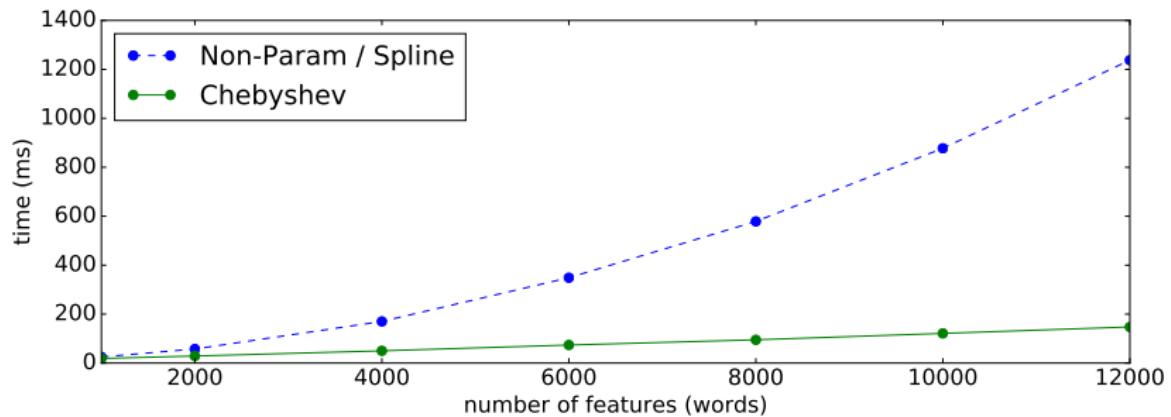
Accuracies of GC32 with different graph constructions on 20NEWS.

Architecture	8-NN on 2D Euclidean grid	random
GC32	97.40	96.88
GC32-P4-GC64-P4-FC512	99.14	95.39

Classification accuracies with different graph constructions on MNIST.

20NEWS: training time

Defferrard, Bresson, and Vandergheynst 2016



Make CNNs practical for graph signals !

Spline: $\hat{g}_\theta(\Lambda) = B\theta$ where B is the cubic spline basis
(Bruna, Zaremba, Szlam, and LeCun 2014)

Application: semi-supervised learning

Kipf and Welling 2016

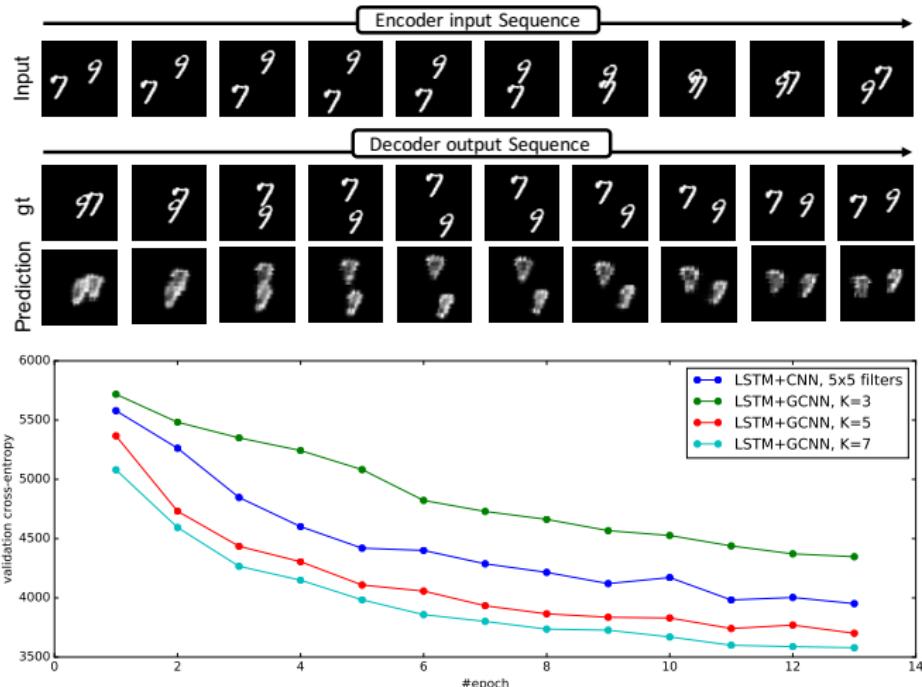
- ▶ Problem: Semi-supervised classification.
- ▶ Architecture: two graph convolutional layers.
- ▶ Filters: first-order approximation, i.e. $K = 1$.

Method	Citeseer	Cora	Pubmed	NELL
ManiReg	60.1	59.5	70.7	21.8
SemiEmb	59.6	59.0	71.1	26.7
LP	45.3	68.0	63.0	26.5
DeepWalk	43.2	67.2	65.3	58.1
Planetoid	64.7 (26s)	75.7 (13s)	77.2 (25s)	61.9 (185s)
GCN (this paper)	70.3 (7s)	81.5 (4s)	79.0 (38s)	66.0 (48s)

Application: time-varying graph signals

Seo, Defferrard, Bresson, and Vandergheynst 2016

Stack a RNN on top of a graph ConvNet.



Conclusion

1. Non-Euclidean data.
2. Extrinsic vs intrinsic formulation.
3. Intrinsic: spatial vs spectral formulation.
4. Efficient formulations are important for Machine Learning!
5. Some results showing versatility of modeling with graphs.

Further research

- ▶ Model definition
- ▶ Applications

Thanks for attending NTDS

and

Merry Christmas!